

Building Next-Generation AI Industrial Competitiveness

— New Competitive Dynamics Revealed
by the U.S.–China AI Race



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Introduction

Frontier AI Accelerates, Opening a New Stage of Competition

Since April 2026, leading U.S. AI companies, including Anthropic, OpenAI, Meta, and xAI, have successively introduced next-generation models with advanced multi-step reasoning and autonomous coding capabilities, significantly raising the performance frontier of AI. At the same time, Chinese companies—including Moonshot AI (Kimi), Alibaba (Qwen), Zhipu AI (GLM), and DeepSeek—have achieved rapid performance gains, particularly through open models, and are releasing models that increasingly approach the capabilities of their U.S. counterparts. With U.S. leaders continuing to introduce increasingly capable models, the U.S.–China race to develop frontier AI is becoming more intense.

This rapid acceleration of frontier AI is fundamentally reshaping the focus of AI competition. The race is no longer simply about who can “build” the most capable AI models. It is increasingly about who can deploy increasingly sophisticated AI across society and industry—and convert it into economic and social value—most rapidly and effectively. This represents the emergence of a new stage of competition that extends well beyond the United States and China to countries and companies around the world. In other words, future competitive advantage will depend not simply on “countries and companies that have AI,” but increasingly on “countries and companies that create value with AI.”

This paper examines the current state of the U.S.–China AI race and the evolution of its competitive dynamics through four perspectives: **the resources and hardware foundations that create AI intelligence; the capabilities of AI models; the ecosystem for industrial deployment; and the ability to convert AI into economic value.** It then extracts the underlying mechanisms of competitiveness revealed by the U.S.–China competition and draws broader global implications for building next-generation AI industrial competitiveness.

1. Building AI Industrial Competitiveness

— Resources, Intelligence, Industrialization, and Value

The U.S.–China AI race has traditionally been assessed through individual indicators such as AI research papers and patents, talent, startups, investment, GPUs, and frontier models. These are important indicators of the resources and capabilities that underpin AI innovation, but many represent inputs or intermediate outcomes rather than the ultimate value delivered to the economy and society. AI industrial competitiveness cannot be captured by a single KPI. Comparing individual metrics in isolation therefore provides only a partial view of the competitive landscape.

This paper views AI industrial competitiveness through a four-layer structure that traces how resources are transformed into intelligence, industrial applications, and ultimately economic and social value (Figure 1).

Layer 1 — Capital & Computing Infrastructure:

The resource and hardware foundation required to create AI intelligence, including capital, energy, data centers, and AI chips.

Layer 2 — AI Intelligence:

The layer in which these resources are transformed into advanced and useful AI capabilities. Frontier model performance and innovation in models and software are at the core of this layer.

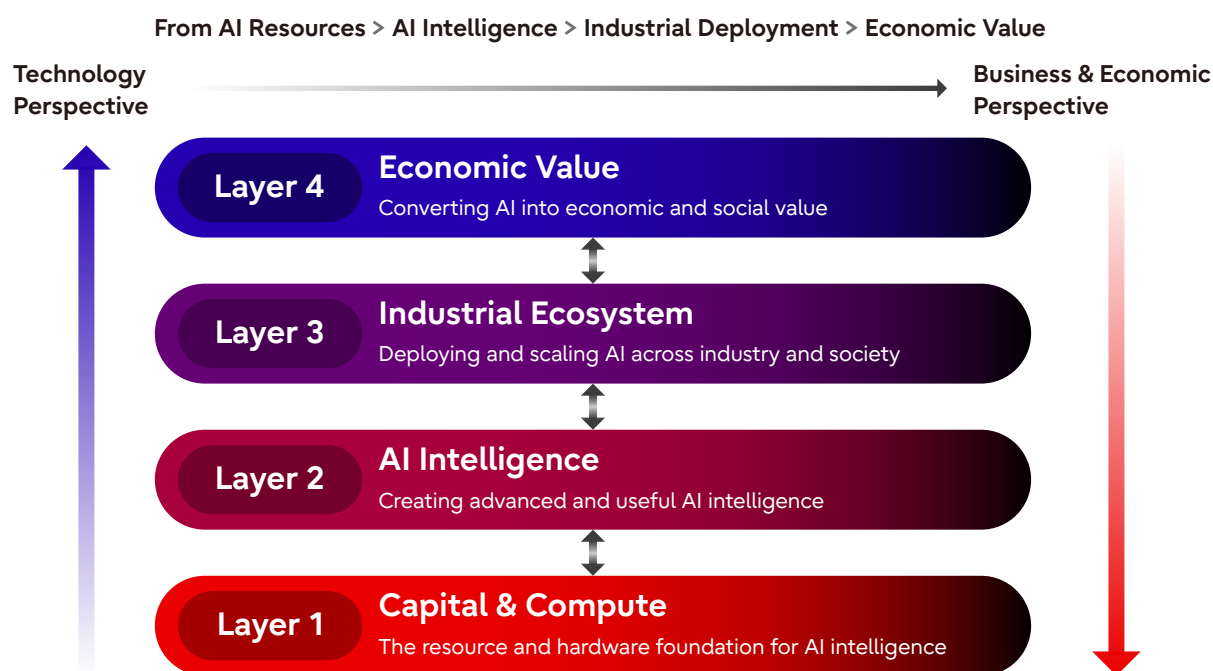
Layer 3 — AI Industrialization:

The application and deployment layer through which AI intelligence is integrated into diverse industries and business processes and scaled across the economy.

Layer 4 — Economic Value Creation:

The stage at which AI is ultimately converted into economic and social value through productivity gains, new products and services, and the creation of new industries.

Figure 1 Four-Layer Value Creation Structure for AI Industrial Competitiveness



Source: Author

Importantly, these four layers do not necessarily operate as a linear sequence from Layer 1 to Layer 4. Countries and companies differ in the layers where they possess competitive strengths, how they deploy resources, where they apply AI, and how they ultimately create value. AI industrial competitiveness therefore cannot be measured simply by the scale of capital or computing resources invested, or by intermediate outputs such as research papers and patents.

What matters is how effectively these resources and capabilities are transformed into advanced and useful AI intelligence, deployed across industries and the real economy, and ultimately converted into economic and social value. **The ability to connect these layers—and to accelerate the flow of value across them—is itself becoming a source of competitive advantage.**

The United States and China do not necessarily need to build competitive advantage through the same layers or along the same pathways. **What matters is how each leverages and combines its respective strengths to transform AI intelligence into sustainable economic value.**

2. Building AI Intelligence Foundations

— DCs, Computing, and Power

The starting point of AI competition is not the development of sophisticated models, but the ability to secure the physical infrastructure required to train and run them. Today, three elements are becoming critical to AI competitiveness: ① **data center (DC) infrastructure**, ② **AI computing hardware**, and ③ **stable and sustainable power supply**.

Table 1 compares the U.S. and China across their physical AI infrastructure, computing capacity, power foundations, and the key bottlenecks and responses associated with scaling AI infrastructure.

Table 1 U.S.–China AI Data Center Competitiveness

Comparison Item	United States	China
1. Number of DCs (May 2026)	5,427 (46% of global total)	449 (3.8%)
2. Total DC Capacity (Power, May 2026)	29.2 GW (43.1% of global total)	8.5 GW (12.6%)
3. DC IT Load (16-bit Compute Capacity, July 2025)	High-end AI compute: 74% global share	High-end AI compute: 14% global share
4. DC Electricity Consumption (2025)	312.6 TWh	170 TWh
5. DC Share of National Electricity Consumption (2025)	4,200 TWh / ~7.4%	10,368.2 TWh / ~1.6%
6. Key Challenges	• Rapid DC capacity expansion • Power and grid-connection constraints • Grid-connection delays and regulatory constraints	• Limited access to advanced GPUs • Advanced-chip supply constraints • Regional mismatch between power and compute demand
7. Key Responses	• Large-scale investment led by hyperscalers • Nuclear power, including behind-the-meter and SMRs	• Strengthening domestic AI semiconductors • Resource reallocation through “East Data, West Computing” • Emerging infrastructure such as subsea data centers

Note: “16-bit compute capacity” refers to the computing performance of FP16 and BF16 used for AI training and inference.

Source: Research and compilation by the author.

China Faces Constraints on Advanced GPUs and Semiconductor Manufacturing Equipment

As Table 1 shows, the United States currently has a significant lead over China in the physical infrastructure supporting AI computing, including the number of DCs, total capacity, and IT load. This reflects the rapid expansion of AI-optimized DCs equipped with high-performance GPUs, backed by massive investments from hyperscalers such as Microsoft, OpenAI, Google, and Meta.

China, by contrast, faces significant constraints on access to advanced GPUs and semiconductor manufacturing equipment as a result of U.S. export controls. China is seeking to offset these constraints by strengthening domestic AI chips, clustering multiple chips, and optimizing hardware and software as an integrated system. Huawei is a prominent example, integrating large numbers of Ascend chips and improving effective computing capabilities at the system level, including servers, high-speed interconnects, AI clusters, and software—rather than relying solely on the performance of individual chips.

The key implication is that competition in AI infrastructure is not determined solely by **how many of the most advanced chips a country can secure**. The ability to **extract greater effective computing capacity from constrained hardware resources** is becoming an equally important source of competitive advantage.

Power Constraints Are Emerging as a New Bottleneck in the United States

The power landscape presents a different challenge. While China's DC electricity consumption is already roughly two-thirds that of the United States, DCs account for a substantially larger share of national electricity consumption in the United States. The rapid growth of AI and DC demand is therefore turning power supply itself into a new constraint on U.S. AI infrastructure expansion.

In the AI era, DC competitiveness is no longer determined simply by the availability of land, buildings, and servers. As facilities approaching 1 GW of power demand emerge, **generation capacity, transmission networks, grid interconnection, cooling, and coordination with local communities** are all becoming potential constraints on expansion. In response, U.S. hyperscalers are accelerating large-scale investment while securing diverse power sources, including nuclear, natural gas, and renewables. Initiatives that procure electricity directly from existing nuclear plants or other generation assets without relying on the transmission grid—so-called **behind-the-meter** arrangements—are emblematic of this trend.

China faces a different challenge: a geographic mismatch between where power is generated and where computing demand is concentrated. In response, China is reallocating computing resources to regions with abundant power through initiatives such as **“East Data, West Computing,”** while transmitting electricity from western regions to the eastern coast through **“West-to-East Power Transmission.”** China is also exploring emerging infrastructure technologies, including subsea data centers.

These U.S. and Chinese examples suggest that securing and reallocating power and computing resources in the AI era will increasingly require **public-private collaboration that combines private investment with government policy, power infrastructure, and regional resources.**

AI Infrastructure Competition Is Shifting from “Scale” to “Quality and Efficiency”

Another important shift is the increasing decentralization of AI infrastructure. Hyperscale DCs currently attract most of the attention because of their role in large-scale model training. However, as AI use expands toward inference, AI agents, physical AI, and sovereign AI, edge and smaller on-premises DCs are also likely to become more important. This will create a new challenge: **how to network and operate increasingly distributed computing infrastructure efficiently.**

Moreover, outside the United States and China, many countries and regions can obtain advanced IT hardware, including GPUs, to a certain extent. Maximizing value creation from AI will therefore depend not simply on adding more GPUs or power, but on how much effective AI processing capacity can be extracted from each unit of power and computing resources, depending on the use case.

AI infrastructure competition is likely to shift from a **race for quantity**—how many DCs, how much power, and how many chips can be secured—to a **race for quality and efficiency**—how much AI intelligence can be generated from limited resources. Beyond advances in hardware performance, the ability to improve the effective performance of the overall AI infrastructure, including the efficiency of models and software discussed in Chapter 3—will become an increasingly important source of next-generation AI industrial competitiveness.

3. Creating Advanced and Useful AI

— Performance, Cost, Efficiency, and Practical Utility

Building on the AI infrastructure discussed in Chapter 2, how far can the United States and China translate their computing foundations into advanced and useful AI intelligence? This section compares leading AI models across four dimensions: **Intelligence, Cost, Efficiency, and Context Window** (see Table 2).

Table 2 Top 10 AI Models in Intelligence — U.S.–China Comparison
Intelligence, Cost, Efficiency, and Context Window (As of September 11, 2026)

Top 10 Lab Models	Artificial Analysis Intelligence Index	Cost per Intelligence Index task	Output tokens per second	Context window (tokens)
1. Claude Fable 5.1 (max with fall back) 	53 (#1 / 200) (closed and open)	\$7.63 (#74 / 200)	66.3 (#76 / 200)	1M
2. GPT-6 Astra (max) 	53 (#3 / 200)	\$3.26 (#66 / 200)	54.4 (#109 / 200)	1M
3. Muse Spark 1.3 (max) 	48 (#13 / 200)	\$1.60 (#50 / 200)	196.9 (#11 / 200)	1M
4. GLM-5.3 (max) 	45 (#1 / 113,open)	\$2.01 (#31 / 113)	59.4 (#36 / 113)	1M
5. Grok 4.6 (high) 	44 (#20 / 202)	\$1.25 (#36 / 202)	53.3 (#112 / 202)	500K
6. Kimi K3 (max) 	44 (#2 / 113,open)	\$2.00 (#30 / 113)	37.9 (#57 / 113)	1M
7. Gemini 3.8 Flash (high) 	41 (#28 / 200)	\$1.24 (#42 / 200)	262.1 (#4 / 200)	1M
8. Qwen3.8 2.4T A95B 	40 (#4 / 113,open)	\$2.16 (#32 / 113)	38.2 (#55 / 113)	984K
9. DeepSeek V4.1 Flash (max) 	40 (#6 / 113,open)	\$0.27 (#19 / 113)	194.3 (#5 / 113)	1M
10. MiniMax-M3 	30 (#16 / 113, open)	\$0.51 (#24 / 113)	88.5 (#15 / 113)	1M

 USA  China

Source: Prepared by the author based on data from Artificial Analysis Intelligence Index v4.3 (September 2026).

AI Model Development: From U.S.–China Leadership to a Global Competition

Artificial Analysis has expanded its evaluation beyond conventional model performance to assess the ability to perform increasingly complex and practical tasks, reflected in its **Intelligence Index v4.3**.

As Table 2 shows, the Top 10 is dominated by U.S. developers—including Anthropic, OpenAI, Meta, xAI, and Google—while Chinese developers such as Z.ai (Zhipu AI), Moonshot AI, Alibaba, DeepSeek, and MiniMax have also entered the ranks. Although the United States retains a substantial lead, **China's catch-up is becoming increasingly evident**.

U.S.-based Thinking Machines Lab's Inkling (xhigh) and France's Mistral Medium 3.5 are also recognized among the leading models. While the AI model race remains led by the United States and China, **the competitive landscape is steadily broadening beyond the two countries**.

From “Open vs. Closed” to Competition over Model Portfolios

Model deployment strategies are also evolving. Traditionally, the U.S. and China have been characterized as favoring closed and open-weight models, respectively. U.S. AI leaders have generally focused on proprietary models at the cutting edge, while Chinese developers have actively leveraged open-weight models to accelerate technology diffusion and attract developers.

This binary view, however, is becoming less adequate for describing the current competitive landscape. Even as leading frontier models increasingly favor closed approaches, lightweight, specialized, and edge-oriented models are also being offered as open-weight models. The strategic question is therefore no longer simply “**Open or Closed?**” but **how to combine different degrees of openness across model tiers, use cases, customers, and markets**.

AI model competition is thus shifting from a binary choice between open and closed models toward building the optimal model portfolio for different strategic purposes.

From Model Performance to Competition on Cost and Efficiency

Alongside the race to develop increasingly capable models, the ability to deploy AI at lower cost and greater efficiency is becoming equally important.

DeepSeek is emblematic of this shift. Its emergence in early 2025 demonstrated the potential to achieve capabilities comparable to leading U.S. models with substantially fewer computing resources. Chinese developers have sought to extract greater performance from constrained resources through techniques including **GPU utilization optimization, mixture-of-experts (MoE) architectures, and lower-precision computing.**

These developments have also influenced U.S. providers, accelerating the introduction of lower-cost, lightweight models and intensifying price competition. The focus is increasingly shifting from simply maximizing AI usage to **selecting and operating the right model for each use case and optimizing the trade-off between performance and cost.** Chinese providers, meanwhile, are also placing greater emphasis on profitability, narrowing the price gap between leading U.S. and Chinese models.

The Competitive Frontier Is Shifting toward “Advanced and Useful AI Intelligence”

Practical utility depends on more than intelligence and price. The ability to handle long contexts enables models to process large volumes of documents, code, and data, expanding their applicability to complex tasks. Leading models have already reached context windows in the million-token range. Output speed is equally important, affecting user experience, real-time processing, and the execution efficiency of AI agents. In these dimensions, differences are increasingly determined by individual model design and use cases rather than by national origin.

The AI race is therefore no longer simply about **building the “most intelligent model.”** What increasingly matters is **how much intelligence can be delivered at the right cost and efficiency, and how quickly and effectively increasingly complex tasks can be performed.** The ability to combine these dimensions and translate them into **advanced and useful AI intelligence for real-world applications** is becoming a critical source of competitive advantage.



4. Industrializing AI

— From Building AI to Putting AI to Work

The “AI Intelligence” created at Layer 2 generates economic value only when delivered to businesses and consumers through cloud and AI services. This chapter examines the competition to **deploy and scale AI across industry and society**.

Cloud Services: U.S. Leaders, Chinese Challengers

U.S. providers hold more than 70% of the global cloud market, led by AWS, Microsoft, and Google. Neo-clouds such as CoreWeave and Nebius Group are also expanding rapidly by supplying large-scale GPU capacity, reinforcing U.S. leadership in AI infrastructure.

Chinese providers—including Alibaba, Huawei, and Tencent—hold roughly 10% of the market, primarily in China, while expanding in Southeast Asia and potentially across Belt and Road markets. Export controls on advanced GPUs have encouraged a different model: Baidu, Huawei, and Alibaba combine domestic AI accelerators with cloud infrastructure, while government-led “**Intelligent Computing Centers**” (**Zhijisuan Zhongxin**) provide distributed compute capacity to local AI startups.

The emergence of GPU cloud spot markets in 2026 further points to the **commoditization of AI compute**. New models are also emerging, such as Hong Kong-based Antimatter, which combines open models with globally distributed micro-data centers to address sovereign AI needs.

The competitive frontier is therefore shifting from cloud capacity alone to the ability to **combine models, compute, and infrastructure into the right operating environment for each use case**.

From AI Agents to “Digital Labor”

Enterprise AI is moving from answering questions to **delegating complex tasks to AI**. Leading companies are going further, embedding AI agents as **“digital labor” with defined roles, permissions, behavioral rules, and KPIs**, while redesigning workflows and governance around them.

Table 3 Managing and Evaluating “Digital Labor”: Six Leading U.S. and Chinese Companies

Company	Positioning of AI	Human Management	KPI / Performance	Key Characteristics
BNY (US)	Digital Employee	Human managers are assigned.	Performance is reviewed and continuously optimized.	AI is given tasks, accounts, and other resources, and integrated into the organization like a human colleague.
ServiceNow (US)	AI Specialist / Autonomous Workforce	Humans provide supervision and feedback.	Real-time monitoring of performance, workload, uptime, and other metrics.	AI is managed as a workforce, with learning and continuous improvement built into the process.
Goldman Sachs (US)	AI Agent / AI Workforce	Humans design skills and provide feedback.	Productivity, accuracy, and other metrics are analyzed and improved.	AI is taught firm-specific “tacit knowledge” and adapted to the organization’s way of working.
Tencent Cloud (China)	AI Agent / Digital Workforce	Roles, responsibilities, permissions, and tasks are defined.	Success rate, latency, error rate, cost, token usage, and other metrics.	Agents are treated as team members and evaluated like other contributors to team performance.
Alibaba Cloud (China)	Digital Employee	Employee IDs, roles, and access permissions are defined.	Skills, activities, permission usage, and other attributes are managed.	The digital workforce structure is explicitly defined as: ID → Skills → Task Allocation → Access Permissions.
Yum China (China)	Digital Agent / Digital Employee	Humans and AI are managed within the same work framework.	Speed, quality, customer satisfaction, and other metrics.	Human and digital workers are compared and evaluated against the same standards, enabling continuous improvement of both.

Source: Research and compilation by the author.

As Table 3 shows, leading U.S. companies such as BNY, Goldman Sachs, and ServiceNow increasingly treat AI as a **new organizational member**, managing it much like human labor through defined roles, responsibilities, and performance metrics. Major end users such as JPMorgan and Walmart are also leading agent development and deployment, highlighting an increasingly **end-user-driven model of AI implementation**.

In China, technology leaders such as Alibaba and Tencent are building and deploying digital-worker systems at scale—including identity, permissions, skills, task allocation, and KPIs—and then commercializing them as external services. At the same time, more traditional approaches remain common in other industries, creating a two-tier market between AI managed as a workforce and AI managed primarily as an IT efficiency tool.

Meanwhile, **Solopreneurs** and China's **OPC (One Person Company)** model are emerging as new organizational forms in which a small number of people coordinate large numbers of AI agents. Open-source digital workers such as OpenClaw are also gaining rapid adoption.

AI is thus evolving from **software that assists people into a new form of labor that performs defined roles and tasks**, potentially reshaping organizational design itself.

From the Digital World to the Physical World: The Rise of Physical AI

AI industrialization is now extending from the digital world into the physical world. Advances in sensors, AI chips, batteries, generative AI, world models, and VLA are enabling robots to evolve from task-specific machines into systems that **integrate perception, reasoning, and action**. Humanoids are a leading example, with potential applications across factories, warehouses, and commercial facilities designed for human workers.

According to Omdia, China's Agibot, Unitree, and UBtech accounted for approximately **78% of the ~14,000 humanoids shipped globally in 2025**, while U.S. leaders Figure AI, Tesla, and Agility Robotics each accounted for around 1%. Early deployments also differ: U.S. companies have focused primarily on manufacturing and logistics, while Chinese companies are pursuing a broader range of applications, including education, research, entertainment, retail, healthcare, and hospitality.

**Figure 2 Technology Maturity and Breadth of Capability:
Six Leading U.S. and Chinese Humanoid Companies**

● Advanced ● Broad ● Partial / Limited

Item \ Company	Figure AI (US)	Tesla	Agility Robotics	Agibot (China)	Unitree	Ubtech
Development and Commercialization						
Form Factor and Mobility	●	●	●	●	●	●
Payload and Lifting Capacity	●	●	●	●	●	●
Object Manipulation	●	●	●	●	●	●
Perception and Autonomous Locomotion	●	●	●	●	●	●
AI Learning	●	●	●	●	●	●
Customer Engagement						
Ease of Customization	●	●	●	●	●	●
Production and Deployment Scalability	●	●	●	●	●	●
Commercial Impact	●	●	●	●	●	●

Source: Reconstructed and developed by the author based on research and analysis, with reference to Omdia's humanoid robotics heatmap.

Figure 2 provides a simplified comparison of the **technology maturity and breadth of capability** of leading U.S. and Chinese humanoid companies.

The competition is therefore not only between companies but also between **different models of industrialization**. U.S. companies tend to emphasize AI capability, technical maturity, safety, and reliability, with more staged commercialization. Chinese companies tend to accelerate market formation through broader model offerings, lower prices, mass production, and early deployment.

The competitive frontier, however, is converging. What will increasingly matter is **how reliably AI-driven perception, reasoning, and action can operate in the field—and how rapidly they can be manufactured and deployed at scale**. Companies that combine advanced AI integration with rapid mass production and field learning are likely to gain an advantage in commercializing Physical AI.

The race should not, however, be viewed solely through a U.S.–China lens. Japan and Europe also possess distinctive strengths: world-class manufacturing capabilities; high standards for quality and safety; strong vertical customer bases in automotive, heavy industry, logistics, and medical devices; and sophisticated component and supply-chain ecosystems built through decades of industrial robotics.

With stronger policy support and a more dynamic startup ecosystem, these advantages could create new opportunities to **bridge advanced technology with high-quality industrial deployment**.

5. Converting AI into Value

— From Productivity Gains to Maximizing Business Value

As massive investments in AI continue, the ultimate question is how much economic and business value AI actually creates. With AI advancing rapidly, quantifying return on investment (ROI) remains a work in progress, and some estimates suggest that only around 20% of companies can clearly demonstrate AI's contribution to revenue. At the same time, leading companies are beginning to measure AI value through their own KPIs.

United States: “Bottom-Up and Financially Disciplined”

At JPMorgan and ServiceNow, efforts are under way to link AI value directly to measurable business outcomes and financial impact. JPMorgan has established business outcome metrics for more than 600 AI use cases in production, evaluating them across four categories: ① time savings, ② cost reduction, ③ revenue contribution, and ④ value creation. Time savings, however, become economic value only when the capacity released is redirected to other activities or revenue-generating work, highlighting the importance of converting efficiency gains into tangible value.

By aggregating value across individual use cases, JPMorgan reports that AI-generated value has reached approximately **\$2 billion**, approaching the level of its annual AI investment.

This reflects a **bottom-up, financially disciplined approach**, in which the impact of individual use cases is measured, and ROI is built from the ground up. Companies typically begin by demonstrating results in areas where causality is easier to establish, such as cost reduction and operational efficiency, and then expand toward top-line value through monetization of AI capabilities and customer engagement.

China: “Top-Down and Strategically Speed-Oriented”

In China, the government's “**AI Plus**” policy emphasizes rapid AI deployment across industries to raise productivity across the broader economy. Corporate performance is therefore assessed not only through financial metrics but also through KPIs aligned with industrial policy, including AI-enabled workload, cost reduction, innovative applications, and shorter new-product development cycles.

Table 4 compares how JPMorgan and Industrial and Commercial Bank of China (ICBC), two leading banks in the United States and China, create and evaluate value from AI.

Table 4 AI Value Creation: Use Cases and Outcomes at Two Leading U.S. and Chinese Banks

Company	Representative Use Cases	Key KPIs	Key Outcomes & Results
JPMorgan (U.S.)	• COiN: Automated review of commercial loan contracts • AI fraud & check-fraud detection • Cash Flow Intelligence: Corporate cash-flow forecasting	• Time Recovery: Contract review time • Cost Reduction: Reduction in legal costs • Value Creation: Total enterprise-wide AI value	• More than \$1.5 billion in annual value creation across the firm • Cash-flow forecasting tool expanded free of charge to ~2,500 companies
Industrial and Commercial Bank of China (ICBC)	• AI-RPA: Branch and back-office automation • Automated document generation for loan reviews and audits • Digital supply-chain finance	• Time Recovery: Time savings and processing capacity • Cost Reduction: Workforce savings and operational efficiency • Revenue & Customer Value: Revenue growth, risk avoidance, customer satisfaction and UX	• AI processed an annual workload equivalent to ~55,000 person-years • 25× productivity improvement in applications such as AI-based credit-card approval • AI-generated code exceeded 30% of total code

Source: Research and compilation by the author.

Where JPMorgan builds up the impact of individual AI use cases to calculate “**value creation**,” ICBC places greater emphasis on **how far AI can expand processing capacity beyond existing operational limits**, while tracking efficiency, cost reduction, customer engagement, and other measures. A distinctive feature is the use of workload-based metrics, such as “**tens of thousands of person-years of equivalent workload**” and “**hundreds of millions of tasks**” (“task” referring to a unit of processing required to achieve a specific business objective).

This reflects a **top-down, strategically speed-oriented approach**: rather than focusing primarily on short-term ROI, Chinese companies seek to deploy AI rapidly as a low-cost, scalable source of productivity, expanding market share and customer reach. KPIs are also adapted flexibly to changing market conditions. In the first half of 2026, for example, greater emphasis shifted from equivalent person-years of workload to the number of use cases deployed and customers served by AI services, reflecting a focus on maximizing the benefits of AI at scale.

From an AI-Driven Productivity Revolution to Maximizing Value Creation

Although the approaches of U.S. and Chinese companies differ, their objectives are increasingly converging. In existing industries, the focus is shifting beyond efficiency and productivity gains toward creating value on **both the bottom and top lines** through customer engagement, risk management, and other applications.

Ultimately, the U.S.–China AI race is no longer simply about **who can “build” the most capable AI**. It is increasingly about **who can convert AI Intelligence into greater economic and business value—faster, at greater scale, and more broadly**.

Achieving this requires a shift toward **AI-first**, with AI positioned at the core of management and business operations. This means rapidly redesigning organizations and workflows, innovating business models, and—above all—enabling executives, managers, and employees to shift their mindsets and adapt to working with AI.

Conclusion

Toward AI-First Companies That Maximize Value Creation — Three Implications for Business Leaders

This paper has examined the U.S.–China AI race to identify the structure of AI competition, its sources of competitive advantage, and how companies are converting AI into economic and business value. The central implication is clear: companies must move **from having AI to creating value with AI**. Three implications follow for business leaders.

① Reframe AI as a New Business Resource and Workforce — Not Just IT

Traditionally, economic growth has been viewed as the creation of value through the deployment of assets, human capital, and technology. In the age of AI agents, AI can increasingly expand its potential value through learning, augment human capabilities, and autonomously perform tasks within defined roles, making it a new form of **intelligent workforce**.

The strategic question is therefore how to treat AI as a **new business resource** and optimize its combination with human capabilities to create value.

② Redesign the Organization, Work, and KPIs around “AI Value Creation” — Not AI Adoption

Companies have spent years testing AI's technological potential through adoption initiatives and PoCs. Today, leading companies are moving beyond experimentation and demonstrating measurable economic and business value. For companies aspiring to become **AI-first**, the starting point is no longer “How do we adopt AI?” but “**What value can we create with AI?**”

This requires redesigning the organization, workflows, KPIs, and business models around AI value creation. There is no universal formula for KPIs or value creation. Each company must design its own model around its strategic objectives, knowledge and data assets, and customer needs—and continuously adapt it as conditions change.

③ Proactively Address the Emerging Risks of Advanced AI Intelligence

As AI models rapidly advance and the global frontier expands, new risks are emerging, including guardrail circumvention and unauthorized access to external systems. Governance and regulatory frameworks are evolving, but companies should not wait for regulation to catch up.

AI trust and security should be designed as an **end-to-end capability**—from early threat detection and prevention to containment and recovery. As AI-enabled attacks become more sophisticated, companies must also build AI-native defenses and response capabilities, making **proactive AI risk management an integral part of enterprise competitiveness**.

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- [Token-Centric Management in the Age of AI Agents: A New Management Framework for Competitive Advantage](#) (September 2026)
- [The Semiconductor Industry Redefined by AI](#) (July 2026)
- [Drug Discovery 2.0: How AI-Native Biopharma Is Redefining Drug Discovery and Competitive Advantage](#) (July 2026)
- [The Evolution of AI Workforce in Manufacturing](#) (June 2026)
- [Rebuilding the Foundations of Competitiveness and Trust for the Intelligent Systems Era](#) (May 2026)

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